Human and Ecological Risk Assessment: Vol. 9, No. 4, pp. 1023-1057 (2003)

Multicriteria Bayesian Analysis of Lower Trophic Level Uncertainties and Value of Research in Lake Erie

Jong Bum Kim,[1] Benjamin F. Hobbs,[1*] and Joseph F. Koonce[2]
[1]Department of Geography & Environmental Engineering, The Johns Hopkins University, Baltimore MD 21218. [2]Department of Biology, Case Western Reserve University, Cleveland, OH 44106

ABSTRACT

Human activities have severely disrupted the Lake Erie ecosystem. Recent changes in the structure of the lower trophic level associated with exotic species invasions and reduced nutrient loading have created ecological uncertainties for fisheries management. Decisions that naïvely assume certainty may be different and suboptimal compared to choices that consider uncertainty. Here we illustrate how multiobjective Bayesian decision analysis can recognize the multiple goals of management in evaluations of the effect of ecological uncertainties on management and the value of information from ecological research. Value judgments and subjective probabilities required by the decision analysis were provided by six Lake Erie fishery agency biologists. The Lake Erie Ecological Model was used to project the impacts of each combination of management actions and lower trophic level parameter values. The analysis shows that explicitly considering lower trophic level uncertainties can alter decisions concerning Lake Erie fishery harvests. Of the research projects considered, investigation of goby predation of zebra mussels (*Dreissena* sp.) and lakewide estimation of secondary production appear to have the greatest expected value for fisheries management. We also find that changes in the weights assigned to management goals affects decisions and value of information more than do changes in probability judgments.

Key Words: Bayesian analysis; decision trees; multicriteria decision making; zebra mussels; ecosystem modeling; Lake Erie; ecosystem management; fisheries management.

* Corresponding author: Tel(voice): 410-516-7092, Tel(fax): 410-516-8996; bhobbs@jhu.edu
Manuscript received May 20, 2002; revised manuscript accepted October 10, 2002

1080-7039/03/$.50

INTRODUCTION

Natural resource management is subject to inherent uncertainty because of natural variability and incomplete understanding of ecosystem structure and function. Explicit consideration of uncertainty in management can result in more prudent decisions and better-expected performance than if uncertainty is disregarded (Reckhow 1994a; Ellison 1996; Peterman and Anderson 1999). Further, rigorous assessment of the value of decreasing uncertainty through research requires explicit consideration of the likelihood of alternative possible outcomes of research and the effects of that information on decisions. However, because ecosystems produce a range of services that are valued in diverse ways by societal groups, "value" is necessarily a multidimensional notion. Decision analysis is a tool for considering both uncertainty and the multiple dimensions of value; it can contribute to better decisions by helping managers to structure the problem, balance risks, and compare options based on outcomes and expressed preferences (Keeney and Raiffa 1976; Clemen 1995).

Cultural stresses over the past 175 years have resulted in substantial uncertainty concerning the future of the Lake Erie ecosystem (Hobbs *et al.* 2000). By the 1950s, agricultural fertilizers, untreated human waste, and industrial byproducts were major stresses. In addition, by the late 1960s, overfishing caused the extinction of the blue pike and dramatic declines in the populations of other native Lake Erie species such as walleye, whitefish, herring, and sturgeon (Koonce *et al.* 1996). Meanwhile, the 1970 discovery of mercury in walleye tissue prompted a temporary moratorium on walleye fishing. Subsequently, the US and Canada cooperated to implement quota management for the Great Lakes fisheries. This action, together with pollution abatement, caused the walleye population to recover from its severely depressed status in the 1960s (Hatch *et al.* 1987). Yet, the highly successful recovery of fisheries in the 1980s did not continue into the 1990s.

The reasons for the decline of Lake Erie's fisheries in the 1990s are unclear. As noted by Locci and Koonce (1999), three general explanations have been proposed: (1) declining productivity of the lake resulting from reductions of phosphorus inputs; (2) declining primary productivity associated with the effects of zebra mussels on nutrient cycling and phytoplankton density, which may have lowered the availability of food for fish and thus caused a decline in fish production; and (3) a predator-prey imbalance in the 1980s, which may have caused predator-prey oscillations and declines in fish abundance during the 1990s.

An important source of this uncertainty is ignorance concerning how zebra mussels impact energy and nutrient flows in the lower trophic level of the Lake Erie ecosystem (encompassing phytoplankton, zooplankton, and zoobenthos). Ecologists have proposed several distinct hypotheses concerning these impacts, and their implications for fisheries. Such scientific debate adds to the already considerable uncertainty faced by fishery managers resulting from, *e.g.*, error-laden estimates of population sizes and weather-dependent recruitment rates (CGLRM 2000). Despite these uncertainties, US and Canadian fishery agencies must make decisions annually about, for example, maximum takes, season length, and allowable equipment.

Explicit risk analyses have not been used to identify robust fish harvest policies for Lake Erie. Although there are several studies (*e.g.,* CGLRM 2000) that characterize the uncertain state of present knowledge (including the zebra mussels' influence on the lower trophic level), none have (1) quantified the uncertainty implied by the existence of different hypotheses about the zebra mussel's impact, (2) systematically compared management alternatives while recognizing that uncertainty, or (3) estimated the value to management of additional research that could decrease uncertainty.

The object of this paper is to use multicriteria Bayesian analysis to quantify uncertainties about the Lake Erie ecosystem and show how they can be considered in fisheries management and ecological research planning. Two concerns—conflicting goals and scientific uncertainty—play key roles in our analysis. The ubiquity of competing interests and uncertainty in ecological management is well recognized (*e.g.*, Ludwig *et al.* 1993). Systematic consideration of tradeoffs using multicriteria analysis can help make decisions more defensible and consistent (McDaniels 1995). In addition, Bayesian analysis can express uncertainty in quantitative terms and incorporate new knowledge gained from monitoring and research (Sainsbury 1991; Ellison 1996).

Goal conflicts in ecological management have been analyzed before using various multicriteria decision analysis methods. These methods differ in how they elicit and structure people's preference judgments, and how those judgments are used to rank alternatives (Clemen 1995; Hobbs and Meier 2000). Such methods can make decisions involving complex tradeoffs more comprehensive, transparent, and consistent. As examples of applications, multiattribute value and utility methods have been used to compare options for fisheries management and eutrophication mitigation (Reckhow 1994b; McDaniels 1995; Anderson *et al.* 2001), water conservation (Kindler 1998), natural reserve selection (Rothley 1999), and water quality improvement (Ridgley and Rijsberman 1992). The methods of ELECTRE and goal programming have been applied to reservoir operation (Harboe 1992), water allocation (Bella *et al.* 1996), and fisheries management (Mardle *et al.* 2000).

There is also a significant literature on the use of experiments and Bayesian analysis to update knowledge about environmental systems and to evaluate information gathering activities (*e.g.*, Reckhow 1990; Sainsbury 1991; McAllister and Peterman 1992; Ellison 1996; Wolfson *et al.* 1996; Hobbs 1997; Dakins 1999). The basic theory underlying Bayesian value of information analysis was proposed by Lindley (1956). The advantage of Bayesian analysis is that the approach is a practical and theoretically attractive way for updating beliefs about uncertainties in light of information from empirical observation, modeling, or expert judgment. This theory has been applied to environmental decision problems such as contaminated site remediation (Dakins *et al.* 1996), monitoring for water quality management (Varis and Kuikka 1999), greenhouse gas mitigation (Manne and Richels 1991), Lake Erie water level management (Venkatesh and Hobbs 1999), and wetlands management under climate change uncertainty (Bloczynski *et al.* 2000). As an example, Walters and Green (1997) used this approach to quantify the value of information for fish stocking. They considered experiments involving varying stocking rates among different lakes in order to obtain better estimates of how growth or survival decrease with increasing stocking density. Such iterative Bayesian updating processes are one approach for implementing the adaptive management paradigm (Walters and Hilborn 1976; Walters 1986).

However, unlike the analysis in this paper, previous studies of the value of ecological information in the literature have generally been based on a single decision criterion, not fully reflecting the multiple conflicting goals of management. Further, we consider a wide range of research projects directed at several parameters of an ecological model, while most previous Bayesian analyses in ecology have emphasized a single critical parameter of a population model. Our application shows how value and probability judgments from a group of managers can be integrated into a risk assessment of fisheries management and ecological research, and how decisions can be sensitive to those judgments. We also quantify the value of explicitly considering uncertainty.

The plan of the paper is as follows. In the methods section, we present the elements of our decision analysis approach, including probability models, the multicriteria utility model, an ecological model, and fish harvest management and ecological research options. Procedures for eliciting necessary value and probability judgments from fishery managers who participated in two workshops are summarized. The methods section also describes how the resulting decision tree is solved in order to calculate optimal management and research strategies, the expected cost of ignoring uncertainty (ECIU), and the value of perfect and imperfect information (EVPI, EVII). The results section summarizes the results of the application, including sensitivity analyses.

METHODS

In the first methodology subsection below, we provide an overview of the structure and products of our decision analysis. In the subsequent subsections, we explain several methodological components including Bayes' Law, multicriteria decision analysis, and decision trees. We then describe how we obtain optimal strategies, ECIU, EVII, and EVPI. Details are provided on the fishery alternatives, the Lake Erie Ecological Model, lower trophic level hypotheses and their prior probabilities, the research options and likelihoods of research outcomes, and finally the performance criteria and weightings used to evaluate the options.

Structure and Products of the Decision Analysis

The first task of a decision analysis is to describe the choices to be made, when they are made, what information is available, and what decision criteria are to be applied. We structure the Lake Erie fishery management problem as having two decision stages. At the first stage, we decide whether a research project should be undertaken and, if so, which one. The chosen project(s) should represent the best balance of research cost and the value of reduced uncertainty. We denote the possible research projects as e_1, e_2, … and the decision of no research as e_0; thus, $\underline{E} \equiv \{ e_h, h = 0,1,.,H \}$ is the set of available projects. Then, at the second decision stage, we choose a fishery management policy a_s from the available options $\underline{A} \equiv \{ a_s, s = 0,1,.,S \}$, based in part on the knowledge obtained from the research. As a first approximation, we assume that the policy is to be implemented for a time horizon of 50 years. Thus, we do not consider adaptive policies that are adjusted depending on estimated populations and other information; however, the proposed framework could accommodate a more sophisticated analysis of that type. In reality, the Lake

200642.pgs 1026 6/18/03, 10:47 AM

Erie Committee of the Great Lakes Fishery Commission does adjust harvest regulations from year to year, based on informal analyses of changing knowledge and priorities. However, rule-based exploitation policies (*e.g.*, Koonce and Shuter 1987) that vary exploitation adaptively have not been implemented, and methods to estimate fixed exploitation rates remain the accepted practice.

We represent model uncertainty by probability distributions over a set of parameters $\underline{\Delta} = \{\delta_{n,}\ n=1,2,\ldots, N\}$ of the lower trophic module of the Lake Erie Ecological Model (LEEM, described below). Distinct values of the parameters can represent alternative hypotheses about the effects of zebra mussels on lower trophic level nutrient and energy flows. We use discrete probability distributions for the parameters, denoting the possible values of δ_n by $\delta_{n1,} \ldots\ \delta_{nm}, \ldots, \delta_{nM(n)}$, where $M(n)$ is the number of possible values of δ_n. In order to simplify the assessment of probabilities, we assume that the distributions are independent. Bayesian analysis, which we describe later, requires assessments of both prior distributions for these parameters, as well as likelihood probabilities that describe the distribution of research outcomes conditioned on the values of the parameters. These distributions were provided as direct judgments by the fishery managers participating in our study.

The valued services and attributes of the Lake Erie ecosystem that will be used as decision criteria are a vector $\underline{X}(a_s, \underline{\Delta})$. This vector is calculated by LEEM for each combination of values of the management decision a_s and lower trophic level parameters $\underline{\Delta}$. Multicriteria utility functions that translate these criteria into a scalar measure of performance $U(\underline{X}(a_s, \underline{\Delta}))$ were elicited from the fishery managers using procedures described later in this article. Optimal fishery management and research decisions for each utility function can be derived by maximizing its expected value over the possible values of the uncertain parameters.

A decision analysis such as the one in this paper can yield several potentially useful products. In this application, we calculate the following:

1. Optimal strategies; given the uncertainties $\underline{\Delta}$ and the information that results from research, we can identify which research and management options maximize the expected utility of $\underline{X}$.

2. The performance penalty resulted from disregarding uncertainty (ECIU), equaling the difference in the expected performance of a naïve strategy developed assuming certainty, and a more sophisticated strategy that considers uncertainty (Morgan and Henrion 1990).

3. The value of information: the expected improvement in performance associated with decreased uncertainty through new research (Lindley 1956; Benjamin and Cornell 1970; Morgan and Henrion 1990). This includes two quantitative indices: the first is the value of imperfect information (EVII), equal to the difference between the expected pay-off of (1) the optimal decision given improved information from research about $\underline{\Delta}$ and (2) the optimal decision without further information. The second index is the worth of perfect information (EVPI), the difference between the expected performance of (1) the optimal decision given perfect knowledge of $\underline{\Delta}$ (or some of its components) and (2) (again) the optimal decision without more informa-

tion. EVPI is an easily calculated upper bound to EVII, and can be used to bound the benefits of research.

Bayes' Law: Reducing Uncertainties in $\underline{\Delta}$

Bayes' Law is the keystone of Bayesian decision analysis. Bayes' Law allows us to use information, such as research outcomes, to update beliefs about scientific uncertainties (expressed here as parameter distributions). Let the outcome of a research project e_h be designated Z_h, with possible realizations $\{Z_{hk},\ k = 1,2,..,\ K(h)\}$. Bayes' Law uses outcomes to update prior probabilities $P(\delta_{nm})$ of the parameters, yielding posterior probabilities $P(\delta_{nm}|Z_{hk})$:

$$P(\delta_{nm}|Z_{hk}) = P(Z_{hk} \mid \delta_{nm})P(\delta_{nm}) / \Sigma_p P(Z_{hk} \mid \delta_{np})P(\delta_{np}) = P(Z_{hk} \mid \delta_{nm})P(\delta_{nm}) / P(Z_{hk}) \tag{1}$$

where $P(Z_{hk} \mid \delta_{nm})$ is the likelihood of outcome k given that δ_{nm} is the true state of parameter δ_n, and $P(Z_{hk})$ is the unconditional probability of outcome Z_{hk}. Eq. 1 can be generalized to the case where $\underline{Z}_h$ and $\underline{\Delta}$ are vector quantities.

The value of a research project is assessed by comparing the expected performance of management developed using the posterior probabilities $P(\delta_{nm} \mid Z_{hk})$ to the expected performance of the optimal strategy based just on the prior probabilities $P(\delta_n)$. Of course, research involves costs and the decision analysis must weigh improved performance against this expense.

Multicriteria Utility Functions $U(\underline{X}(a_s, \underline{\Delta}))$

The selection of decision criteria $\underline{X} = \{x_{i,}, \ldots i = 1,..,I\}$ is an important step in multicriteria decision analysis (Barton and Sergeant 1998). According to multicriteria decision theory, the set of criteria should be both comprehensive and measurable while avoiding conceptual overlap (Keeney and Raiffa 1976). (We discuss the criteria selection process in more detail later.) The values of these criteria are calculated by an ecological model and depend on the alternative chosen and the assumed parameter values: $\underline{X}(a_s, \underline{\Delta}) = \{x_1(a_s, \underline{\Delta}), \ldots, x_I(a_s, \underline{\Delta})\}$. There are many methods for translating multiple criteria into a single index of desirability (Hobbs and Meier 2000). We choose to apply Multiattribute Utility Theory (MAUT) (Keeney and Raiffa 1976; Clemen 1995). MAUT's advantages include a large number of documented applications along with a normatively appealing set of axioms concerning how people evaluate alternatives under risk.

Multicriteria utility functions can be constructed as follows. First, a single criterion utility function $u_i(x_i)$ is assessed separately for each criterion x_i. These functions represent relative preferences concerning different values of x_i and have a range of 0 to 1, representing the worst and best values, respectively. These functions also capture the user's attitudes toward risk; for instance, whether alternatives with smaller variances are preferred (risk aversion). Several techniques, such as the certainty equivalent procedure, can be used to elicit single criterion utility functions from managers (Keeney and Raiffa 1976; Clemen 1995).

The second step involved in creating utility functions is to aggregate the criteria, permitting overall comparison of the alternatives a_s. A simple aggregation is the additive utility function:

$$U(\underline{X}(a_s, \underline{\Delta})) = \Sigma_i w_i\, u_i(x_i\,(a_s, \underline{\Delta})). \qquad (2)$$

where w_i represents the weight for criterion i ($\Sigma_i w_i = 1$), and $U(\underline{X}(a_s, \underline{\Delta}))$ is the overall utility of alternative a_s, given state of nature $\underline{\Delta}$. The major assumption underlying the additive form is additive independence, which applies if preferences between two distinct alternatives $\underline{X}^1$ and $\underline{X}^2$ depend only on the marginal probability distributions of the x_i within an alternative, and not their joint distribution (Keeney and Raiffa 1976). Several techniques to assess weights are available, *e.g.*, the Analytic Hierarchy Process and the gamble, swing, and trade-off methods (Watson and Buede 1987). The trade-off method is often favored because it derives weights from observed choices among alternatives, as opposed to asking directly for numerical weights whose meaning may be ambiguous. For this reason, we asked the fishery managers participating in our study to use the trade-off approach; details of the procedure are given by Anderson *et al.* (2001).

Each participant went through the above steps, creating their own utility function, which we use to choose the option that maximizes his or her expected utility $E_{\underline{\Delta}}[U(\underline{X}(a_s, \underline{\Delta}))] = \Sigma_{\underline{\Delta}} P(\underline{\Delta}) U(\underline{X}(a_s, \underline{\Delta}))$. However, the numerical difference in expected utility between two alternatives (say, a_1 and a_2) is not directly interpretable, since utility functions are, strictly speaking, only ordinal scales. Fortunately, a difference in expected utility can be converted to an equivalent difference in one of the criteria x_i by the following procedure. Let a_1 be preferred to a_2 (*i.e.*, $E_{\underline{\Delta}}[U(\underline{X}(a_1,\underline{\Delta}))] > E_{\underline{\Delta}}[U(\underline{X}(a_2,\underline{\Delta}))]$). Let $\underline{X}^{(i*)}$ be defined as a vector of length I consisting entirely of zeroes except for the ith element whose value is x_i*. The value of this element is calculated by solving the following equation for $\underline{X}^{(i*)}$:

$$E_{\underline{\Delta}}[U(\underline{X}(a_1,\underline{\Delta}))] = E_{\underline{\Delta}}[U(\underline{X}(a_2,\underline{\Delta}) + \underline{X}^{(i*)})] \qquad (3)$$

This x_i* can then be interpreted as the amount that a_2 would have to improve in criterion i in order to make a_2 as attractive as a_1. Here we use annual walleye sport harvest (x_2) to gauge the difference between alternatives. By this measure we might calculate that a given alternative is preferred to another option by an amount equivalent to an increased catch of, say, 10 tons of walleye/year. A similar procedure is used below to express value of information and cost of ignoring uncertainty in terms of an easily interpreted attribute. Note that this procedure generalizes the more common decision analysis technique of expressing all values in dollar terms.

Decision Tree Analysis to Define Optimal Strategies

Trees are used in decision analysis to graphically portray the structure of the decision problem. They are also used to solve for the optimal decision strategy using the method of "folding back" (also called backwards dynamic programming). Figure 1 is a schematic of the decision tree for the Lake Erie research project evaluation problem. The tree flows from left to right through time.

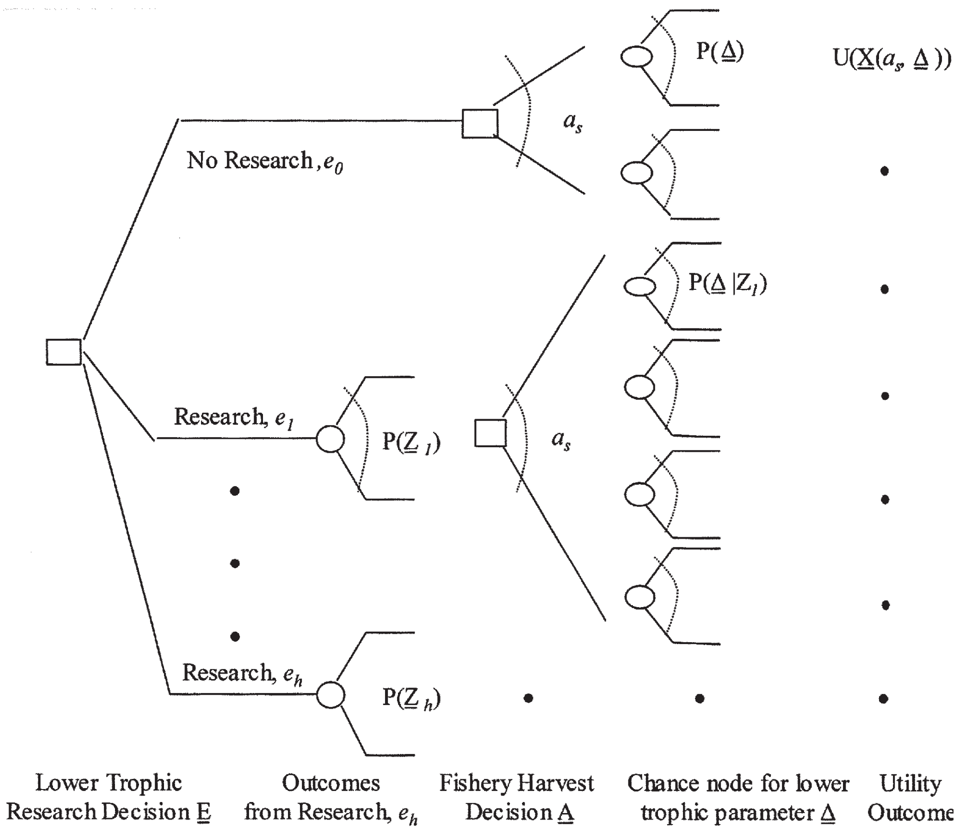


Figure 1. Decision tree for fisheries management with research options.

A decision tree has three basic elements.

1. Decision nodes (squares) represent decision points. Each alternative (here, an element of $\underline{E}$ or $\underline{A}$) is represented by a separate arc connected to the right side of a decision node. In the case of Figure 1, two decision stages are shown, representing (1) what research projects $e_h \in \underline{E}$ can be undertaken and then (2) what fisheries management actions $a_s \in \underline{A}$ can be implemented. A full tree shows a separate branch for each alternative; we use the schematic for simplicity.

2. Chance nodes (circles) represent random events, with an arc for each possible realization (an element of either $\underline{Z}$ or $\underline{\Delta}$). Probabilities are attached to each arc, and the sum of those probabilities for a given node must be one. Here we have two types of chance nodes: one for model parameters $\underline{\Delta}$ and the other for outcomes of research $\underline{Z}$. Note that the chance node for $\underline{\Delta}$ that follows implementation of a research project shows posterior probabilities $P(\underline{\Delta}|\underline{Z}_h)$ from Bayes' Law (Eq. 1), conditioned on the research project outcome $\underline{Z}_h$.

3. Outcomes $\underline{X}$ and their utility $U(\underline{X})$.

The optimal management action a_s results from maximizing $E_{\underline{\Delta}}[U(\underline{X}(a_s,\underline{\Delta}))]$, given available information in the form of the distribution of $\underline{\Delta}$. The most effective research project is that which yields the highest value of $E_{Z_h}[E_{\underline{\Delta}}[U(\underline{X}(a_{opt|Z_h}, \underline{\Delta}))|\underline{Z}_h]$. This is the expected performance of the optimal strategies under the different research outcomes $\underline{Z}_h$, weighted by the probability of each outcome $P(\underline{Z}_h) = \Sigma\underline{\Delta}\ P(\underline{Z}_h|\underline{\Delta})P(\underline{\Delta})$. $a_{opt|Z_h}$ is the optimal management decision, given outcome $\underline{Z}_h$.

The optimal strategy and its expected performance are obtained by folding back the decision tree. The procedure starts from the branches farthest to the right and moves leftward (backward in time). At each node encountered, one of the following operations is performed: either calculate the expected performance (chance node), or determine the alternative with the highest expected performance, noting its expected utility (decision node). This procedure continues until the calculation is completed for the leftmost node of the network; the optimal research and management strategy has then been found, defined as the optimal choice for each of the decision nodes.

Cost of Ignoring Uncertainty and Value of Information

We have just introduced one product of a decision analysis: the optimal decision strategy. Other products include the quantification of the expected penalty, if any, if uncertainty is disregarded (ECIU) and the value of information (EVII and EVPI). The procedures used to calculate each of these three concepts is defined below.

ECIU: The expected cost of ignoring uncertainty compares the expected performance of two strategies: (1) a naïve strategy developed assuming that a nominal value for $\underline{\Delta}$ will accrue with probability 1; and (2) an optimal strategy developed considering the full range of possibilities and their probabilities. This represents the expected loss of performance when a decision is made as if there is no risk. The procedure for calculating ECIU is as follows (Morgan and Henrion 1990):

1. Define a nominal (deterministic) value of $\underline{\Delta}$, calling it $\underline{\Delta}_{naïve}$. This may be some "base case" value of $\underline{\Delta}$, or, alternatively, its expected value.

2. Define the optimal strategy, $a_{naïve}$ under the base case assuming that probabilities of every realization $\underline{\Delta}$ are zero except $\underline{\Delta}_{naïve}$:

$$a_{naïve} = \arg\ \mathrm{MAX}_{a_s}\ U(\underline{X}\ (a_s,\underline{\Delta}_{naïve})) \qquad (4)$$

where "arg MAX_a f (a)" denotes the alternative a that leads to the maximum value of f(a).

3. Calculate the expected utility for the naïve strategy defined in Step 2, considering the full probability distribution of $\underline{\Delta}$:

$$E_{\underline{\Delta}}[U(\underline{X}(a_{naïve},\underline{\Delta}))] = \Sigma_{\underline{\Delta}}\ P(\underline{\Delta})\ U(\underline{X}(a_{naïve}, \underline{\Delta})) \qquad (5)$$

4. Define the optimal strategy, a_{opt}, and calculate its expected utility.

$$a_{opt} = \arg \mathrm{MAX}_{a_s}\ \Sigma_{\underline{\Delta}}\ P(\underline{\Delta})\ U(\underline{X}(a_s, \underline{\Delta})) \tag{6}$$

$$E_{\underline{\Delta}}\ [U(\underline{X}(a_{opt}, \underline{\Delta}))] = \Sigma_{\underline{\Delta}}\ P(\underline{\Delta})\ U(\underline{X}(a_{opt}, \underline{\Delta})) \tag{7}$$

5. ECIU is defined as the improvement in the expected utility if a_{opt} is chosen instead of $a_{naïve}$. As noted earlier, a difference in utility between alternatives can be quantified in terms of any particular attribute by Eq. 3. In this case, the equation becomes:

$$E_{\underline{\Delta}}[U(\underline{X}(a_{opt},\underline{\Delta}))] = E_{\underline{\Delta}}[U(\underline{X}(a_{naïve},\underline{\Delta})+\underline{X}^{(i^*)})], \tag{8}$$

in which case ECIU equals the nonzero element of $\underline{X}^{(i^*)}$.

*EVII***:** The expected value of imperfect information is calculated by considering whether research outcomes could affect decisions (Benjamin and Cornell 1970). The calculation recognizes that the information obtained is imperfect (in our case, that the research does not result in error-free parameter estimates). The steps of the method are now described.

Under a given research outcome $\underline{Z}_h$, the best choice at the second decision stage (Figure 1) is:

$$a_{opt|Z_h} = \arg \mathrm{MAX}_{a_s}\ E_{\underline{\Delta}}\ [U(\underline{X}(a_s, \underline{\Delta}))|\underline{Z}_h] = \arg \mathrm{MAX}_{a_s}[\Sigma_{\underline{\Delta}}\ P(\underline{\Delta}|\underline{Z}_h)U(\underline{X}(a_s,\underline{\Delta}))]. \tag{9}$$

The expected utility for that optimal decision at the second decision stage is then

$$E_{\underline{\Delta}}[U(\underline{X}(a_{opt|Z_h},\underline{\Delta}))|\ \underline{Z}_h] = \Sigma_{\underline{\Delta}}\ P(\underline{\Delta}|\underline{Z}_h)U(\underline{X}(a_{opt|Z_h},\underline{\Delta})). \tag{10}$$

Now we can obtain the expected utility of project e_h given all possible project outcomes:

$$E(U(e_h))=E_{Z_h}[E\underline{\Delta}\ [U(\underline{X}(a_{opt|Z_h},\underline{\Delta}))|\ \underline{Z}_h]] = \Sigma_{Z_h}P(\underline{Z}_h)\ [\Sigma_{\underline{\Delta}}\ P(\underline{\Delta}\ |\underline{Z}_h)U(\underline{X}(a_{opt|Z_h}, \underline{\Delta}))]. \tag{11}$$

Meanwhile, for no research project e_0, the optimal management decision and the expected utility for the optimal decision at the second stage are a_{opt} (Eq. 6) and $E_{\underline{\Delta}}[U(\underline{X}(a_{opt}, \underline{\Delta}))]$ (Eq. 7), respectively. The value of information for a project e_h can now be defined as the improvement in the expected utility compared to a_{opt}. Using Eq. 3 to quantify this improvement in terms of some criterion x_i means solving the following equation for $\underline{X}^{(i^*)}$:

$$E_{Z_h}[E_{\underline{\Delta}}\ [U(\underline{X}(a_{opt|Z_h}, \underline{\Delta}))|\ \underline{Z}_h]] = E_{\underline{\Delta}}[U(\underline{X}(a_{opt},\underline{\Delta})+\underline{X}^{(i^*)})]. \tag{12}$$

Similar to the ECIU calculation, EVII will be the nonzero element of $\underline{X}^{(i^*)}$. (Note that the EVII calculation assumes that $U(\underline{X}(a_{opt|Z_h}, \underline{\Delta}))$ *excludes* the cost of the research project itself. This is because EVII refers only to the value of the information, not the expense of obtaining it. Thus, to determine if a project might be worthwhile, one could compare its cost to its EVII in a manner we explain later.) A key theoretical result is that if the research has no chance of changing the decision (*i.e.*, $a_{opt|\ Z_h} = a_{opt}$ for all $\underline{Z}_h$), then EVII=0.

EVPI: The expected value of perfect information is obtained by assuming that new information $\underline{Z}$ permits the user to estimate $\underline{\Delta}$ without error. As a result, the development in Eqs. 9 to 12 can be simplified as follows. First, define $a_{opt|\underline{\Delta}}$ as the optimal strategy given parameter values $\underline{\Delta}$. Then the expected utility if perfect information was available would be $E_{\underline{\Delta}}[U(\underline{X}(a_{opt|\underline{\Delta}},\underline{\Delta}))]$. Comparing this to the expected utility if no information is available $E_{\underline{\Delta}}[U(\underline{X}(a_{opt},\underline{\Delta}))]$ (Eq. 7)) allows us to gauge the value of perfect information. Again using Eq. 3 to quantify this improvement in terms of an attribute x_i, we solve the following equation for $\underline{X}^{(i^*)}$:

$$E_{\underline{\Delta}}[U(\underline{X}(a_{opt|\underline{\Delta}}, \underline{\Delta}))] = E_{\underline{\Delta}}[U(\underline{X}(a_{opt},\underline{\Delta})+\underline{X}^{(i^*)})]. \tag{13}$$

As in the case of ECIU and EVII, EVPI will be the nonzero element of $\underline{X}^{(i^*)}$.

EVPI is an upper bound to the EVII from any real research activities. This upper bound is useful because if EVPI falls short of the cost of a research project, the project cannot be justified by the value of the information it provides. Thus, we can use EVPI to screen research projects— if their cost exceeds their maximum possible benefit, then we do not consider them further.

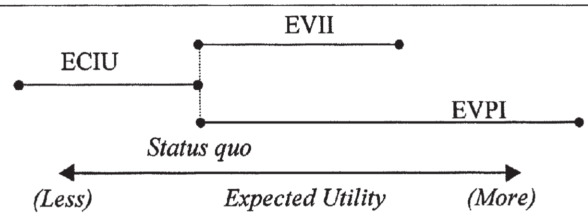
Table 1 summarizes the relationships between ECIU, EVII, and EVPI based on decisions under different information states. The current information state represents the belief without additional information (*i.e.*, prior probability). New but imperfect information can be obtained through research. Perfect information results in the highest possible expected utility (far right), while on the other extreme, ignoring information gives the lowest expected utility.

Lake Erie Ecosystem Decision Alternatives: $\underline{A}$

Ten fishery biologists from US and Canadian resource management agencies participated in two workshops held in Cleveland, OH, in early 2000. The purpose of the workshops was to ask the participants to identify fishery management objectives, alternatives, and uncertainties; to define research projects that could address those uncertainties; and to quantify utility functions and probabilities needed by the decision analysis. In this paper, we report results only for the six managers who were able to attend the entirety of both workshops. These six managers represented agencies from both Canada and several states in the US.

As one of the tasks in the first workshop, the managers identified several classes of fishery management options, including regulations on fishing gear type and commercial and sporting harvest efforts; harvest quotas; stocking; protecting and rehabilitating habitat; and regulating phosphorus discharges. Because regulations and quotas are a responsibility of agencies represented at the workshop, our analysis

Table 1. Summary of relationships between ECIU, EVII, and EVPI.

Information	Decision based on: Naïvely assuming certainty	Present information	Improved information	Perfect information
Current information on uncertainties	Ignored	Included	Included	Included
New information	No	No	Yes	Yes
Errors in new information	N/A	N/A	Yes	No
Expected gain/loss resulting from considering uncertainties and new information				

focuses on those decisions; however, stocking, nutrient, and habitat policies could be considered in a more general study.

In particular, we consider the management of commercial trawling (which targets smelt, *Osmerus mordax*), commercial gill netting (for yellow perch, *Perca flavescens*), and sport harvest (predominantly of walleye, *Stizostedion vitreum*). Management by regulation and quota is modeled as a set of targets for fishing mortality levels, one target for each of the three species. We also assumed that catchability in each of these fisheries varies by age and thus we vary the target mortality by age as well. For simplicity, three levels of each of the targets are considered for each species (high (H), medium (M), and low (L)), or 27 combinations in all; more combinations could be considered at the expense of additional computation time. In 2000, Lake Erie yellow perch target mortality varied by management district averaging 0.4 (yr^{-1}). Walleye target mortality was 0.33 (yr^{-1}). Unlike yellow perch and walleye, Lake Erie fish management agencies do not use a virtual population estimate to derive smelt quotas, and we do not have a target mortality for direct comparison. However, LEEM estimates of target mortalities are broadly consistent with smelt harvests. It is important to note that in addition to impacts on target populations, these decisions can directly impact other species due to by-catch, and indirectly through ecosystem effects (*e.g.*, predation and competitive interactions) (Locci and Koonce 1998). Also, fish management agencies do not use these targets on a strict basis. Quotas derived from these targets are often adjusted qualitatively in response to uncertainty. Hatch *et al.* (1987) review the quota derivation process in more detail.

Ecological Model $\underline{\mathbf{X}}(\mathbf{a}_s, \underline{\Delta})$

We use the Lake Erie Ecological Model (LEEM) to estimate how decisions affect the managers' criteria. LEEM was designed to aid the understanding of ongoing changes and interactions between zebra mussels, fisheries productivity, phosphorus loading, and fisheries management in the Lake Erie system (Koonce and Locci 1995; Locci and Koonce 1999). Using an annual time step, LEEM models age groups of 17 species and dynamically describes prey-predator relationships and the lower trophic level. The model allows users to explore alternative decisions in such areas as phosphorus loading and fisheries management considering the implications of assumptions concerning the parameters and structure of the system.

In theory, it would be desirable to capture uncertainties concerning model structure by considering more than one system model (*e.g.*, as in Ellis 1988). Limiting ourselves to one model may result in a significant understatement of the true uncertainty. However, LEEM is the only available integrated lower trophic level-fisheries model for Lake Erie, and so we attempt to represent structural uncertainties through changes in LEEM parameters. The Appendix lists the equations within LEEM that simulate Lake Erie's lower trophic level. We refer to these equations and their variables in the later discussion of the lower trophic level hypotheses.

Various views among ecologists concerning the role and impact of zebra mussels on phosphorus and energy cycling constitute the scientific uncertainty $\underline{\Delta}$; our decision analysis assesses the implications of that controversy for fishery harvest management. In order to limit the complexity of the probability assessments, we included only five of the LEEM parameters in Δ. These parameters were chosen because they represent the key responses of lower trophic variables to phosphorus and energy inputs. We model this disagreement by allowing the use of different prior probability distributions for LEEM parameters; in particular, we asked each workshop participant to specify their own prior distributions for five LEEM parameters that govern lower trophic level nutrient flows and production efficiencies: ZM_r, Z_{kp}, AZP, AZB, and g_0. Thus, these parameters are the components of $\underline{\Delta}$ whose uncertainty reflects the existence of alternative hypotheses concerning the effect of zebra mussels upon Lake Erie's lower trophic levels. These hypotheses are summarized next.

Alternative Lower Trophic Level Hypotheses for Lake Erie

A wide variety of uncertainties challenge Lake Erie fish managers. Here we focus on a representative set of three mechanisms, considering alternative hypotheses about the effect of zebra mussel invasion on lower trophic level productivity of the Lake Erie ecosystem.

The first mechanism involves the interaction of phosphorus recycling and phytoplankton productivity. Griffith (1999) argues that the net effect of the zebra mussel invasion is an increase in macrophyte production and decrease in phosphorus recycling that combine to lower phytoplankton productivity. In contrast, Culver *et al.* (2000) hypothesize that zebra mussels have increased mineralization of phytoplankton settling into benthic regions and have thus enhanced phosphorus recycling rates; this increased availability of phosphorus for primary production is seen as compensating for the direct effect of increased mussel consumption of algae. The second mechanism concerns the effects of competition between zebra mussels and zooplankton for edible algae. Culver *et al.* (2000) argue that the decline of phytoplankton biomass associated with declining nutrient loads since the 1970s and the zebra mussel invasion have not resulted in a major decline of zooplankton production. In contrast, Heath *et al.* (2000) note that the observed phytoplankton-zooplankton constancy does not extend to the microbial food web, where zebra mussels may have lowered altered energy flux to zooplankton. Finally, the third mechanism addresses effects of zebra mussels on availability of zoobenthos production to fish. Dahl *et al.* (1995) believe that increased zoobenthos production has offset decreases in plankton production, and Dermott (1993) observes that shifts in zoobenthos species composition seem to be towards more edible food items for fish (*e.g.*, from *Unionids* and *Sphaerids* to amphipods).

Representing these mechanisms and their alternative interpretations in LEEM requires overcoming the inherent limitations of LEEM and the lack of more precise models. LEEM is an annual time step model with low resolution of lower trophic level structure. The equations for lower trophic level energy flow, however, have parameters that reasonably aggregate fine-scale spatial and temporal mechanisms on an annual, whole lake basis (see the Appendix). In terms of LEEM parameters, therefore, we use the following parameter adjustments to model each of the mechanisms:

1. *Interaction of phosphorus recycling and phytoplankton productivity.* This effect could be reflected in changes in the relationship of primary production to phosphorus loading, Eq. 14. To accommodate Griffiths' (1999) hypothesis, in particular, decreasing Eq. 14's parameters g_0 and ZM_r relative to LEEM's present assumptions would reflect a reduction in phosphorus recycling. In contrast, the Culver *et al.* (2000) argument would require increasing both parameters.

2. *Competition between zebra mussels and zooplankton for edible algae.* The combination of adjustments in two parameters—lowering Z_{kp} in Eq. 16 and increasing AZP in Eq. 18—would correspond to the mechanism proposed by Culver *et al.* (2000). This would lower the overall effect of zebra mussels on zooplankton productivity, *i.e.*, reduced competition. The alternative interpretation of Heath *et al.* (2000) could be represented by a decrease in AZP (Eq. 18), which decreases the energy flow from pelagic algae to zooplankton.

3. *Higher zoobenthos production.* Increasing the benthic production parameter AZB in Eq. 20, which in turn increases non-mussel zoobenthos productivity $ZooBP_t$, could capture this hypothesis.

Subjective Probability Elicitation: P(δ_{nm})

Each of the above hypotheses describes a distinct set of nutrient and energy interactions, which we capture here by different values of five of LEEM's parameters. Thus, in Figure 1, there would be a series of five chance nodes for $\underline{\Delta}$, one for each of its five components (δ_1=ZM_r, δ_2=Z_{kp}, δ_3=AZP, δ_4=AZB, and δ_5=g_0). To ease the managers' task of specifying probabilities, we allow each parameter to take on just two or three of the following levels: m= high (H), medium (M, base case), or low (L). Given the qualitative characteristics of the hypotheses, we selected numerical values associated with H, M, and L to provide a range of parameter values large enough to be informative without causing unrealistic model behavior. For example, in the case of the relationship between primary production and phosphorus loads, the parameter ZM_r was varied +/-50% from the base case for H and L, respectively. Table 2 shows the assumed LEEM values. Note that some parameters lack a L or H value because no hypothesis suggests lower or higher values, respectively.

The task assigned to each of the fisheries biologists in the workshops was to review and, where appropriate, rephrase the hypotheses, and then assign a prior probability $P(\delta_{nm})$ for each parameter δ_n and each level m that reflects their understanding of the hypotheses and their judgments about the hypotheses' relative likelihood. As explained below, the biologists also chose likelihood probabilities for research outcomes, which we use together with the prior probabilities and Bayes' law to estimate the value of that research. Table 3 shows the average (across the six participants) probability chosen by the managers for each δ_{nm}, along with the ranges of their responses. The wide ranges reflect considerable disagreement concerning the credibility of the hypotheses. The implications of this disagreement are explored in our sensitivity analyses.

A limitation of this study is that we relied on fisheries scientists for these probabilities, as opposed to scientists who study lower trophic level ecology. Nevertheless, we believe that their level of expertise was sufficient to illustrate the value of the Bayesian approach. However, we recommend that actual studies of this type ensure that a more diverse group of experts be relied upon, with at least some members having directly relevant research experience.

Research Projects and Outcome Likelihoods: $\underline{E}$ and $P(Z_{hk}|\delta_{nm})$

The first decision node in Figure 1 represents possible research projects, $\underline{E} = \{e_0, e_1, \ldots, e_H\}$. If a project is undertaken, the prior probabilities $P(\delta_{nm})$ are updated by Bayes' rule (Eq. 1), yielding posterior probabilities, $P(\delta_{nm} \mid Z_{hk})$. Likelihoods $P(Z_{hk} \mid \delta_{nm})$ are required by Bayes Law (Eq. 1) to describe the information about the parameters provided by the potential research projects. In this part of the workshop, the following questions were addressed by the managers:

1. What possible research projects might help discriminate among the hypotheses?

2. What is the likelihood $P(Z_{hk} \mid \delta_{nm})$ of each research outcome, given the true state δ_{nm}?

3. What is the cost and time required for each possible project?

Table 2. LEEM parameter values.

m	δ_n				
	ZM_r [yr^{-1}]	Z_{kp}[yr^{-1}]	AZP[ ]	AZB[ ]	g_0[ ]
High	1.5E-05	-------	1.3E-01	3.8E-02	2.6E+08
Medium	1.0E-05	1.0E+00	1.0E-01	1.5E-02	2.4E+08
Low	5.0E-06	7.0E-01	7.0E-02	--------	2.1E+08

Table 3. Average (across the six participants) prior probabilities P(δ_{nm}) chosen by the managers for each δ_{nm}, along with the ranges of their responses.

m	δ_n				
	ZM_r	Z_{kp}	*AZP*	*AZB*	g_0
High	0.36 (0 - 0.8)	-------	0.42 (0.1 - 0.9)	0.6 (0.1 - 0.8)	0.4 (0 - 0.8)
Medium	0.38 (0.1 - 0.9)	0.63 (0.3 - 0.9)	0.23 (0 - 0.5)	0.4 (0.2 - 0.9)	0.24 (0.1 - 0.3)
Low	0.26 (0 - 0.8)	0.37 (0.1 - 0.8)	0.35 (0 - 0.6)	--------	0.36 (0 - 0.9)

In the workshop, the participants defined 16 research projects. Although in general several projects could be undertaken at once, for the purpose of this illustrative analysis we consider only individual projects. Some of these defined projects were dominated by other projects (*i.e.*, higher costs yet lower reliability of outcomes), while others were very narrow in scope. Because of time limitations, we elicited probabilities from the participants for four of the projects, representing a cross-section of the original 16. Table 4 lists these four, their associated cost and time (averaged across the six participants), and a qualitative indication of the degree to which the participants thought that the projects might provide useful information on each parameter. A darker shading indicates that more information is provided. For instance, primary production monitoring (project *C*) has implications for zebra mussel recycling (first parameter) and primary production (fifth parameter). On the other hand, even though paleolimnological research (project *D*) would also provide information on those parameters, that project's results are judged likely to be less definitive. Yet *C*'s costs in time and money exceeds those *D*, making the latter potentially attractive.

In the second workshop, the fisheries managers provided values of P($Z_{hk} \mid \delta_{nm}$) for the four projects. The research outcomes Z_{hk} are described in very general terms: would the research outcome support a low, medium, or high value of the parameters in question? Table 5 shows an example of the assessed likelihoods: the likelihoods for the parameter ZM_r for project *C*. The values in the table show averages across participants plus their ranges.

This table shows that, on average, the participants felt that project C was more likely than not to yield results consistent with the actual parameter values; this is indicated by values on the diagonal exceeding 0.5. However, some participants anticipated that this particular project would convey little or no information (*e.g.*, nearly equal probabilities in a row).

Selection of Objectives, Criteria, and Weights: $\underline{\mathbf{X}}$ and w_i

In the first of the two workshops, the fisheries managers were asked to define general objectives along with specific numerical criteria that should be used to evaluate fishery management options. Based on their responses, we constructed a

Table 4. **Information provided, cost and time of example research projects. (For each parameter, a darker shading indicates that more information is provided. For example, Project *C* provides more information for δ_5 than Project *D* does.)**

Research Project e_h	Parameter δ_n: δ_1 Zebra mussel recycling ZM_r	δ_2 Zebra mussel production Z_{kp}	δ_3 Zooplankton production efficiency AZP	δ_4 Zoobenthos production efficiency AZB	δ_5 Primary Production g_0	Average estimated cost [$]	Average estimated time [yr]
A. Goby predation on zebra mussel						$194,000	2
B. Lakewide estimates of zooplankton and benthic production						$932,000	5
C. Primary production monitoring						$813,000	6
D. Paleolimnology						$149,000	2

Table 5. **Likelihoods $P(Z_{hk} \mid \delta_{nm})$ for parameter ZMr for project C (Primary Productivity Monitoring) (Mean and ranges across participants (lowest – highest)).**

True state δ (ZM_r)	Outcome of research Z_c: Supports ZM_r = H	Supports ZM_r = M	Supports ZM_r = L	Sum of Means
ZM_r = H	0.6 (0.5 - 0.7)	0.22 (0.1 – 0.3)	0.18 (0 – 0.3)	1
ZM_r = M	0.19 (0.1 –0.33)	0.58 (0.33 – 0.77)	0.23 (0.15 – 0.34)	1
ZM_r = L	0.21 (0 – 0.33)	0.24 (0.1 – 0.33)	0.55 (0.34 – 0.7)	1

hierarchy of objectives and related criteria that capture the range of responses obtained (Figure 2). The overall objective is to maximize ecosystem health and human well-being. That overall goal is subdivided into three categories of objectives: social, ecological, and economic, which are then further divided as explained below. The criteria x_i are LEEM variables that indicate the degree to which the various objectives are furthered.

The social criteria reflect the importance of recreational fishing in Lake Erie; indices of both biomass (biomass of walleye x_1) and total walleye sport harvest (x_2) are used. However, consumption of contaminated fish is also a concern. Since consumption advisories for smallmouth bass are more stringent (1 fish/month) than for walleye (1 fish/week) (Ohio Dept. of Health 1999), we address this concern using average PCB concentration in small mouth bass (x_3).

For the ecological objective, "productivity" refers to total annual productivity; "structure" concerns horizontal trophic relationships having implications for stability of the fish community; "function" refers to vertical trophic relationships relevant to vertical energy flow in the fish community; and "native species" concerns the presence of native types of fish. We adopted the following LEEM variables as quantitative criteria for these objectives: total fish productivity (x_4), the ratio of walleye to percid biomass (x_5), piscivore to planktivore productivity ratio (x_6), and native species to total biomass (x_7), respectively.

Finally, for the economic objective, we considered the harvests of three commercially important species: walleye (x_8), yellow perch (x_9), and smelt (x_{10}).

Turning to the utility function assessment, the first task was to define the range of possible criteria values and a set of single criterion utility functions for each

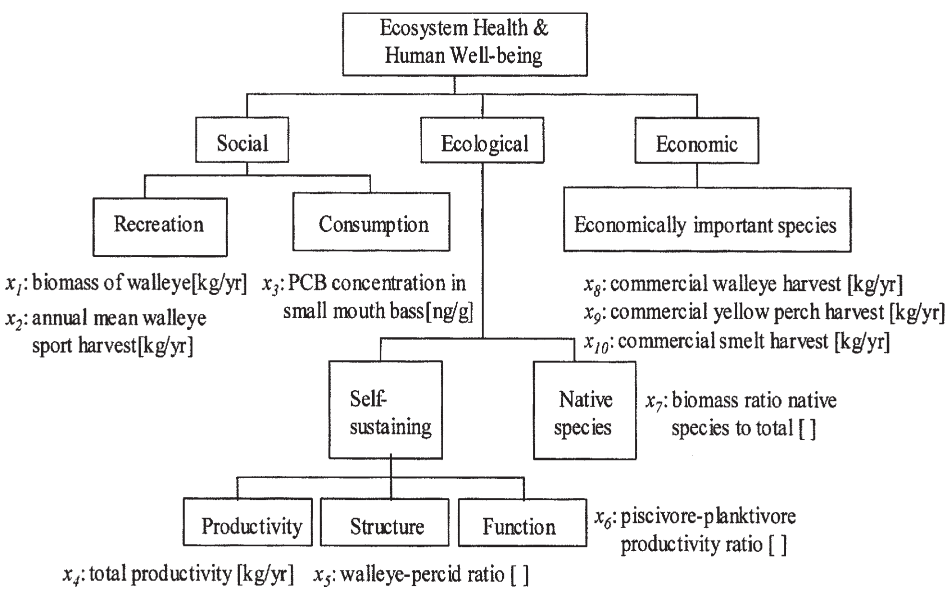


Figure 2. Objectives and criteria x_i chosen by Lake Erie fisheries managers.

person. For simplicity, we assumed that each utility function was linear between the worst (u_i=0) and best (u_i=1) values defined by each participant; if a value of x_i falls outside those ranges, then it was assumed to have a utility of 0 or 1, as appropriate. As for the weights w_i , Table 6 presents the maximum, minimum, and average values across participants for each of the ten criteria. Participants chose weights by describing how much of one attribute they would trade-off for a given improvement in another (Anderson *et al.* 2002; Hobbs and Meier 2000). All the participants assigned higher weight to the recreation criteria and less weight to economic criteria. Because different weights can yield different decisions (*ibid.*; Anderson *et al.* 2001), we examine below the sensitivity of optimal strategies, ECIU, EVPI, and EVII to these results.

An Example of ECIU and Value of Information Calculations

In this section, we provide an example to show how each decision tree component (*i.e.*, the decision alternatives, their performance on the attributes, probability distributions, and effect of research on uncertainties) can affect the optimal decision, ECIU, and value of information. We base the example on the average weights and probabilities provided by the participants. In Table 7, we show four sets of attribute values, one for each combination of two fishery alternatives (out of the 27 possible combinations) and two sets of lower trophic level parameter values (from the 108 combinations). The two alternatives are a_s, = HLH and a_s = HMH, where the three letters refer to the smelt, walleye, and yellow perch target fishing mortality targets, respectively. For the uncertain parameters, we consider { $\delta_{1Medium}$, $\delta_{2Medium}$, $\delta_{3Medium}$, $\delta_{4Medium}$, $\delta_{5Medium}$} and { δ_{1Low}, $\delta_{2Medium}$, $\delta_{3Medium}$, $\delta_{4Medium}$, $\delta_{5Medium}$}. In addition to the parameter values, we also show the values of the single attribute utility function values $u_i(x_i)$ for each alternative, and (in the last row) the weighted sum of those values using the average weights.

The table indicates that judgments about the relative likelihood of different "states of nature" (parameter sets) could affect the decision. In particular, given the second set of parameters, decision HLH has a higher utility than HMH (*i.e.*, U($\underline{X}$(a=HLH)) = 0.5429, while U($\underline{X}$(a=HMH)) = 0.5419). However, under the first set of parameter values, the ranking of the options is reversed.

Likewise, the examination of the attribute values shows that value judgments (weights) can also affect the solution. Consider, for instance, the first and third column of attribute values, which compare HLH and HMH under the medium parameter values. HLH is better in the two walleye attributes (x_1 and x_2), while HMH is as good or better in all the other attributes. This indicates that sufficiently high values of w_1 and w_2 would result in HLH having a higher total utility, while lesser

Table 6. Summary of weights for the 10 criteria.

	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_{10}
Maximum	0.40	0.53	0.13	0.18	0.15	0.13	0.16	0.11	0.11	0.07
Minimum	0.05	0.01	0.02	0.01	0.04	0.05	0.05	0.01	0.01	0.01
Mean	0.17	0.19	0.11	0.10	0.09	0.09	0.11	0.07	0.06	0.03

Table 7. An example of effects of decision and hypotheses on the attributes and utility under mean weights.

Decision	HLH	HLH	HMH	HMH
Hypotheses	$\delta_{nMedium}$, for all n	δ_{nLow} for n=1 $\delta_{nMedium}$ for n=2,3,4,5	$\delta_{nMedium}$, for all n	δ_{nLow} for n=1 $\delta_{nMedium}$ for n=2,3,4,5
x_1 [kg/yr]	2.72E+07	2.48E+07	2.16E+07	1.97E+07
$u_1(x_1)$	0.43	0.39	0.33	0.29
x_2 [kg/yr]	4.71E+06	4.29E+06	3.51E+06	3.18E+06
$u_2(x_2)$	0.53	0.48	0.39	0.35
x_3 [ng/g]	5.71E+02	5.72E+02	5.71E+02	5.72E+02
$u_3(x_3)$	0.92	0.92	0.92	0.92
x_4 [kg/yr]	4.24E+08	3.54E+08	4.39E+08	4.13E+08
$u_4(x_4)$	0.71	0.58	0.74	0.69
x_5 [ ]	5.23E-01	5.21E-01	4.69E-01	4.48E-01
$u_5(x_5)$	0.30	0.30	0.43	0.48
x_6 [ ]	5.33E-02	5.90E-02	4.67E-02	4.54E-02
$u_6(x_6)$	0.96	0.95	0.97	0.98
x_7 [ ]	3.49E-01	3.06E-01	3.57E-01	3.54E-01
$u_7(x_7)$	0.35	0.27	0.36	0.35
x_8 [kg/yr]	1.55E+06	1.41E+06	2.47E+06	2.24E+06
$u_8(x_8)$	0.24	0.21	0.41	0.37
x_9 [kg/yr]	1.78E+06	1.61E+06	3.12E+06	3.08E+06
$u_9(x_9)$	0.26	0.23	0.48	0.48
x_{10} [kg/yr]	1.36E+07	1.05E+07	1.46E+07	1.29E+07
$u_{10}(x_{10})$	0.70	0.54	0.75	0.66
Total Utility (Under mean weights)	0.5429[a]	0.4953	0.5419	0.5209

a. By Eq. 2, 0.5429 = 0.17*0.43 + 0.19*0.53 + 0.11*0.92 + 0.10*0.71 + 0.09*0.30 + 0.09*0.96 + 0.11*0.35 + 0.07*0.24 + 0.06*0.26 + 0.03*0.70, where 0.17, 0.19, *etc.* are the mean (across participants) weights (Table 6).

values for those weights would instead favor HMH. The last line of Table 7 indicates that the average weights would select HLH under those parameter values.

In Figure 3, on the top left side, we show an abbreviated decision tree that ignores uncertainty (*i.e.*, assign a probability of 1 for M for every parameter). As we just stated, the best choice in that case is HLH. On the top right side, which instead considers the full prior distributions of parameters, HMH becomes the best choice. This shows that considering uncertainty matters.

ECIU is the expected amount by which HMH (the best choice under uncertainty) is better than HLH (the naïve choice). HMH has an expected utility that is 0.022 higher than HLH (= 0.5666 – 0.5447, top right side of Figure 3), but the magnitude of this number by itself is difficult to interpret. Therefore, we convert the difference

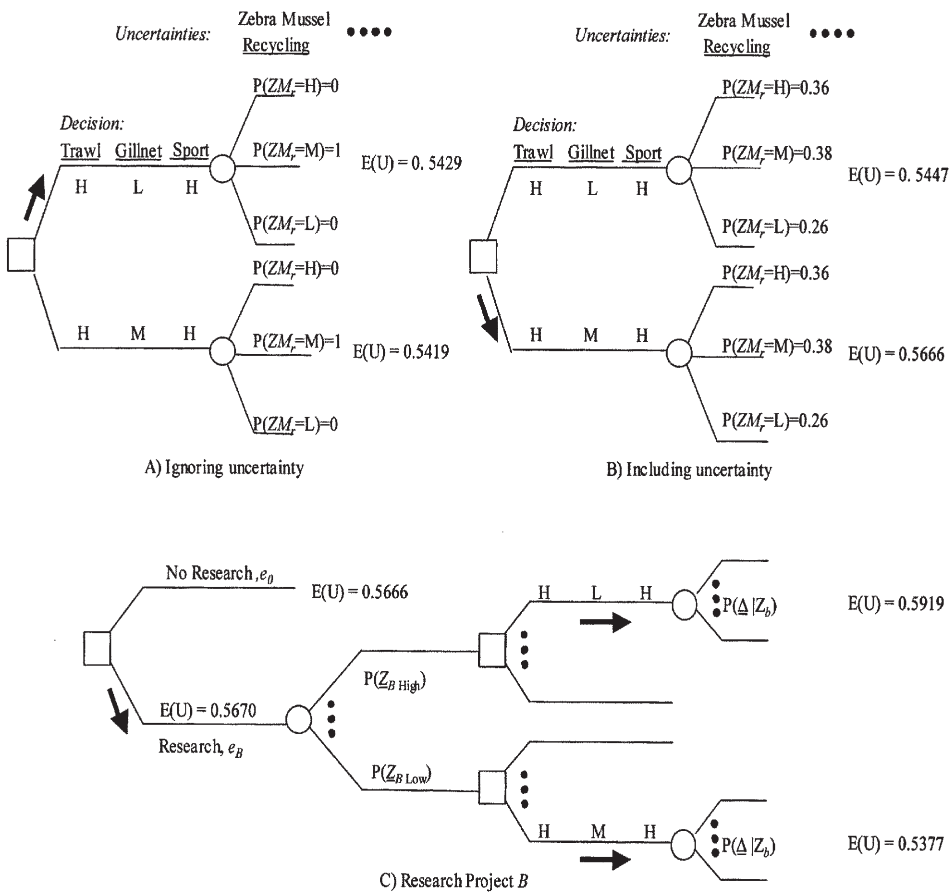


Figure 3. **Decision tree for calculating ECIU and value of research project *B* for lower trophic level. uncertainties under mean group weights and probabilities.**

in utility into an interpretable change in a criterion using Eq. 8. We use walleye sport harvest (x_2) to interpret the difference because it is, on average, the most important attribute (mean $w_2 = 0.19$). The increment of 0.022 in utility is equivalent to 984 tons/yr of walleye sport harvest. To put this value in perspective, the mean walleye sport harvest over 1990 to 1998 was about 2000 tons/yr (2,300,000 fish (LEWTG 1999) times a mean size for 1998 of 0.88 kg (ODW 1999)). This indicates that the cost of ignoring uncertainty in this case is on the order of 50% of the walleye sport harvest.

In the bottom of Figure 3, we illustrate the calculation of the value of information for research project *B* (*i.e.*, Lakewide estimates of zooplankton and benthic production). This project can provide information concerning four of the five uncertain parameters: zebra mussel recycling (ZM_r), zebra mussel production (Z_{kp}), zooplankton production efficiency (*AZP*), and zoobenthos production efficiency (*AZB*). The

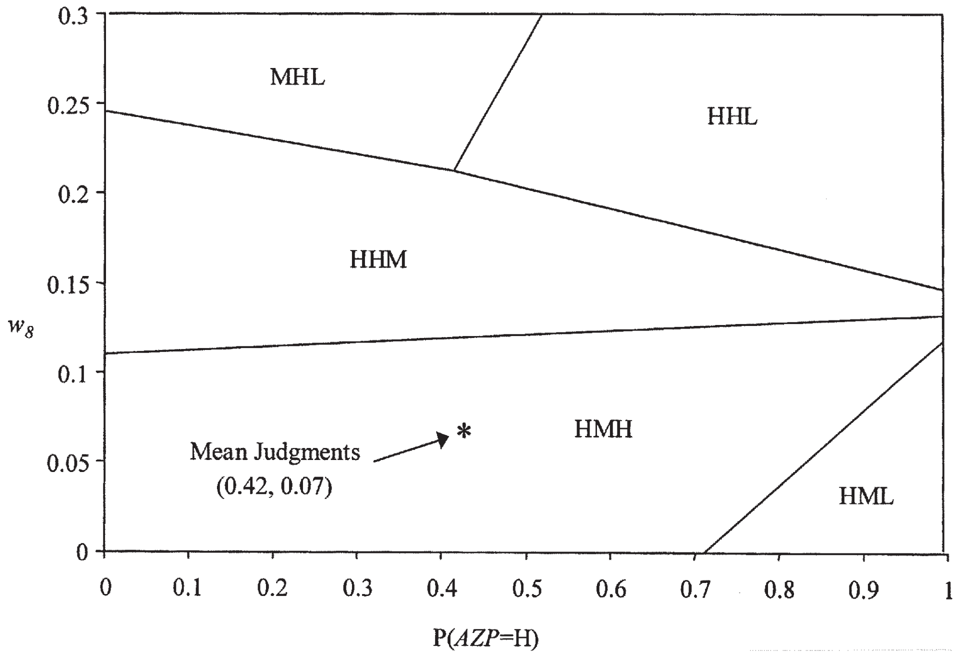


Figure 4. Optimal decisions under varying w_8 and P(*AZP* = H),given mean values across participants for other parameters. (H= High, M= Medium, L= Low. Decisions are for smelt, yellow perch, and walleye, respectively.).

figure reveals that the optimal decision depends on the research project's outcome. One possible outcome is $\{Z_{ZM_r}$=High, $Z_{Z_{kp}}$=Medium, Z_{AZP}=High, Z_{AZB}=High$\}$; that is, that the research indicates that three parameters $\{ZM_r, AZP, AZB\}$ are likely to be relatively high while the other parameter is likely to remain medium. These values are consistent with the enhanced productivity hypotheses of Culver *et al.* (2000) for parameters ZM_r and *AZP* and Dermott (1993) for *AZB*. (Z_{kp} is assumed to remain medium because none of the hypotheses suggest a higher value for it.) This outcome is shown as Z_{BHigh} in the figure. In that case, the optimal choice is $a_{opt|Z_{Bhigh}}$ = HLH, which differs from the optimal strategy if there is no research project (*i.e.*, a_{opt} = HMH). On the other hand, if the project's outcome is more consistent with low values of these parameters, then HMH is instead optimal.

Since the optimal decision depends on the research outcome, that project can have a positive value of information EVII. Figure 3 reveals that the expected utility (over all possible project outcomes) if project *B* is undertaken is 0.0004 higher than if no research project (= 0.5670 – 0.5666). Although that increment of 0.0004 appears small, it is equivalent to 19 tons/yr of walleye sport harvest. The users would then need to compare this research benefit with the project's cost in order to determine whether the project is worth undertaking.

The project has value because it reduces the uncertainty in the parameters and, thus, the performance of the various alternatives. For instance, the high, medium, and low values of parameter ZM_r (0.000015, 0.00001, and 0.000005, respectively), have mean (across participant) prior probabilities of 0.36, 0.38, and 0.26, respectively. Given the mean outcome likelihood probabilities, the posterior probabilities of these same outcomes are 0.61, 0.21, and 0.18, respectively, if project *B*'s outcome is Z_{BHigh}. Thus, parameter uncertainty has decreased. Consequently, uncertainty in the performance of the alternatives will also decrease. For instance, the uncertainty in walleye sport harvest x_2 (as represented by its standard deviation) if HLH is implemented is 1.26E+6 [kg/yr] under the prior probability distribution, but shrinks to 1.09E+6 [kg/yr] under the posterior distribution, given project outcome Z_{BHigh}. As a result of the decreased uncertainty in attribute values, the posterior variance of the overall utility of decision HLH, given an outcome of Z_{BHigh} for project *B*, is $\mathrm{Var}(\mathrm{U}(\underline{\mathrm{X}}(\mathrm{HLH}, \underline{\Delta})) | \underline{Z}_{BHigh}) = 0.0063$. This is one third smaller than the prior variance $\mathrm{Var}(\mathrm{U}(\underline{\mathrm{X}}(\mathrm{HLH}, \underline{\Delta}))) = 0.0092$. It indicates that the information yielded by research allows a decision to be made with more confidence.

RESULTS

In the first subsection below, we discuss optimal fishery management strategies developed without information provided by research, and their sensitivity to weighting and probability judgments. The effect of disregarding uncertainty upon the strategies is also described. Other subsections review ECIU and EVPI results, along with EVII for the four research projects.

Single Stage Optimal Strategies

In this subsection, we provide an overview of how the fishery management strategies depend upon the manager's value judgments (single criteria value functions and weights) and his or her probability judgments about the lower trophic level effects of zebra mussels. Table 8 shows optimal fishing strategies for each of 64 combinations of value judgments (each of the six manager's value judgments, plus the mean weights and equal weights) and prior probability judgments (the six individuals' probability sets, along with the mean probabilities and equal probabilities). Considering all these combinations allows us to compare the relative effect of value judgments versus probability judgments upon the results. For each combination of value and probability judgments, the table displays two optimal strategies: $a_{naïve}$ on top (the optimal strategy under certainty, in which M, the LEEM base case value of each parameter, is assumed to occur with probability 1) and a_{opt} on bottom (optimized instead assuming the stated prior probabilities). When the two strategies are the same, just one entry is shown. As an example, under participant 4's value judgments and probabilities, high (H) target fishing mortalities for smelt and walleye along with a medium (M) target for yellow perch are optimal when the participant considers the uncertainties. In contrast, the naïve strategy (assuming certainty) is instead the restrictive policy of low (L) targets for all fisheries.

The table shows that, of the 64 combinations, $a_{naïve}$ differs from a_{opt} in 22 cases. As a result, we conclude that the expected cost of ignoring uncertainty will be zero for many but not all possible weights and probability judgments. At one extreme, under equal weights or participant 1's value judgments, considering uncertainty makes *no* difference for *any* of the sets of probabilities. On the other hand, for average weights and participants 3 and 6's value judgments, the naïve and sophisticated strategies

Table 8. Optimal target fishing mortalities when uncertainties are ignored or included.

Person's prior probabilities	Person's value judgments							
	1	**2**	**3**	**4**	**5**	**6**	**Equal**	**Mean**
1	HHH	HHH	HLH HMH	LLL HMH	HHH	HLH HMH	HHH	HLH HMH
2	HHH	HHH HHL	HLH	LLL	HHH HMM	HLH	HHH	HLH
3	HHH	HHH HHM	HLH	LLL	HHH HMM	HLH	HHH	HLH HMH
4	HHH	HHH	HLH LLH	LLL HMH	HHH	HLH HMH	HHH	HLH HMH
5	HHH	HHH HHM	HLH	LLL	HHH HMM	HLH	HHH	HLH
6	HHH	HHH	HLH	LLL	HHH	HLH	HHH	HLH
Equal	HHH	HHH	HLH MLH	LLL LLH	HHH	HLH HMH	HHH	HLH HMH
Mean	HHH	HHH	HLH MLH	LLL	HHH	HLH HMH	HHH	HLH HMH

Note: H= High, M= Medium, L= Low. Targets are for smelt, yellow perch, and walleye, respectively. The first decision in each cell is based on deterministic analysis and the second decision in each cell is based on prior probabilities; if decisions identical, only one is shown.

differ for half or more of the sets of probabilities. Hence, ECIU will be zero for equal weights or person 1's values, but potentially large for other sets of value judgments.

Those results indicate that, overall, value judgments affect strategies more than prior probabilities. This hypothesis could be analyzed, *e.g.*, by multivariate ANOVA; however, because our sample of managers is small and nonrandom, we will only discuss qualitative patterns apparent in the table. For example, although there are two weight sets for which probabilities do not matter (all entries are identical in a column), there are no sets of probabilities for which the results are identical for all weight sets. As another indication of the importance of value judgments, different columns diverge in important ways (as an extreme, compare the results for person 4's value judgments with any other person's), but there are no such large differences among the rows. Additional sensitivity analyses (not shown) indicate that the value judgments involved in choosing the w_i are much more important than the value judgments made in choosing the upper and lower bounds of the single criteria utility functions (*i.e.*, the values of the x_i that result in $u_i = 0$ and 1, respectively).

Although value judgments have the greatest effect on strategy choices, probability judgments can still matter in important ways. We demonstrate this through an illustrative sensitivity analysis. With the average probability and value judgments, the optimal decision is HMH (Table 8). Changes in either weights and probabilities can alter this decision. For example, Figure 4 shows how the optimal decision varies if just two judgments (P(*AZP* =H) and w_8) are altered, changing other probabilities and weights proportionately. The elicited average w_8 and P (*AZP*= H) are 0.07 and 0.42, respectively. With a fixed P(*AZP*=H)=0.42, the optimal decision stays at HMH for w_8 in the range [0,0.13]. However, if w_8 exceeds 0.13, the optimal decision would be HHM. Meanwhile, the optimal decision also depends on the selected probability P(*AZP*=H) for most values of w_8.

ECIU Results

ECIU, the expected cost of disregarding uncertainty when it actually exists, can only be nonzero if $a_{naïve}$ differs from a_{opt} (Table 8). Therefore, if a_{opt} equals $a_{naïve}$ for a given combination of value and probability judgments in Table 8, the ECIU will be zero. For example, under participant 1's value judgments and probabilities, Table 8 shows that a_{opt} and $a_{naïve}$ are the same decision, so ECIU = 0. Meanwhile, under participant 4's value judgments and probabilities, the optimal strategy is high (H) target fishing mortalities for smelt and walleye along with a medium (M) target for yellow perch when the participant considers uncertainty. In contrast, the naïve strategy yields a strategy of low (L) targets for all fisheries; therefore, ECIU can be positive.

In Table 9, we calculate ECIU for each of the combinations of value and probability judgments considered in Table 8. As above, ECIU is expressed as the improvement in annual walleye sport harvest needed to equate the expected utility of $a_{naïve}$ and a_{opt} (*i.e.*, Eq. 8). For the 22 cases in which those two strategies differ, the value of ECIU ranges from trivial (a handful of tons) to values well in excess of the annual average sport harvest in 1990-1998 (2000 tons). About half of those values are the same order of magnitude as that harvest. However, for one person (participant 4) this was because the weight for x_2 was small (which inflates the change in x_2 necessary to equate the left and right sides of Eq. 8), not because the utility loss was high. However, some of the high ECIUs occur even though x_2 receives a significant share of the weight (which we define as $w_2 \geq 1/10$). An instance is the average weight column of Table 9. Thus, although we conclude that disregarding lower trophic level uncertainties does not significantly affect the decision in most cases, in some situations the expected penalty is important.

The Maximum Potential Value of Research: EVPI Results

In the previous subsection, we consider only a one-stage decision problem: which fishing policies are optimal, given the present state of information? In contrast, if research would reduce uncertainty, and its benefits (in terms of better management) would exceed its cost, we should consider undertaking that research.

As explained earlier, EVPI is the maximum possible benefit that can be obtained from research; thus, if the expense of research (in $ and time) exceeds EVPI, then the research cannot be justified by just its benefits to management. In Table 10, we summarize EVPI calculated separately for each of two subsets of the parameters in $\underline{\Delta}$, and for all five parameters together; these calculations are made for each of the 64 combinations of value and probability judgments that were also considered in

Table 9. ECIU in terms of sport walleye harvest x_2 (ton/ year).

Person's prior probabilities	Person's value judgments							
	1	2	3	4	5	6	Equal	Mean
1	0	0	670	21,752	0	3,809	0	3,896
2	0	210	0	0	241	0	0	0
3	0	121	0	0	68	0	0	73
4	0	0	203	5,437	0	2,246	0	2,396
5	0	100	0	0	24	0	0	0
6	0	0	0	0	0	0	0	0
Equal	0	0	45	4,444	0	1,191	0	1,446
Mean	0	0	8	0	0	636	0	984
Weights on x_2	0.10	0.15	0.53	0.01	0.11	0.15	0.10	0.19

Tables 8 and 9. These EVPIs are expressed as equivalent changes in annual walleye sport harvest x_2 (Eq. 13). The first of the three EVPIs for each combination is for just the uncertainties that Table 4 indicates are addressed by projects *A* and *B*: ZM_r (mussel phosphorus recycling), Z_{kp} (zebra mussel production), *AZP* (zooplankton production), and *AZB* (*i.e.*, zoobenthos production). Thus, that EVPI is an upper bound for the management benefits of those projects. The second of the EVPIs is for the two parameters that projects *C* and *D* are concerned with: ZM_r and g_0 (the relation between phosphorus loading and primary productivity). The last value is the EVPI for eliminating all five uncertainties (ZM_r, Z_{kp}, *AZP*, *AZB*, g_0).

Table 10 indicates that the EVPIs implied by the managers' judgments are often significant relative to the average annual walleye harvest of 2000 tons/yr in the 1990s. Projects *A* and *B* clearly have higher potential benefits than projects *C* and *D*, as the uncertainties addressed by the former projects apparently have more influence on decisions. Of course, the actual expected benefits of these projects (EVII) could be much smaller, depending on the reliability of their results (as captured in the likelihoods $P(Z_{hk} \mid \delta_{nm})$). Unsurprisingly, the potential value of *A* and *B* is close to the EVPI for all parameters because *A* and *B* address four of the five parameters.

Cursory comparison of Tables 9 and 10 show positive EVPIs for several cases in which ECIU is zero. This is consistent with Table 1, which shows that there is no necessary theoretical relationship between the values of ECIU and EVPI; either can be positive when the other is zero.

To compare the potential value of information for each project with its cost as listed in Table 4, we need to translate the $ cost into an equivalent value of x_2. Based on a review of non-market valuation of Great Lakes fishes (Talhelm 1988) and the application of these results to lake trout fisheries (Koonce *et al.* 1993), we used a value of $12 per fish caught as a basis for comparison. As the research cost is a one-time expense, while the ecological benefits of management are ongoing, an interest rate assumption is needed; here, we use 10%/yr and a 10 year time horizon for the

Table 10. EVPI in terms of walleye sport harvest x_2 (ton/year).

Person's prior probabilities	Research project	Person's value judgments							
		1	2	3	4	5	6	Equal	Mean
1	*A* and *B*	0	66	562	21,582	95	393	0	164
	C and *D*	0	20	285	6,339	18	98	0	40
	All	0	72	597	23,968	101	412	0	174
2	*A* and *B*	0	113	14	6,211	127	109	0	109
	C and *D*	0	24	0	353	0	0	0	14
	All	0	116	17	6,308	127	110	0	109
3	*A* and *B*	0	128	73	11,074	250	308	0	236
	C and *D*	0	26	10	68	81	101	0	102
	All	0	136	77	11,842	251	326	0	239
4	*A* and *B*	0	42	427	22,570	59	339	0	120
	C and *D*	0	5	123	3,688	0	42	0	5
	All	0	46	534	27,287	73	384	0	132
5	*A* and *B*	0	87	0	2,627	199	21	0	28
	C and *D*	0	11	1	1,528	56	12	0	16
	All	0	92	2	3,262	201	25	0	33
6	*A* and *B*	0	39	8	7,563	43	84	0	97
	C and *D*	0	4	0	4,705	3	66	0	82
	All	0	39	9	7,622	44	84	0	98
Equal	*A* and *B*	0	101	373	24,771	128	490	0	161
	C and *D*	0	30	127	8,497	11	181	0	36
	All	0	108	406	26,829	139	512	0	173
Mean	*A* and *B*	0	148	299	19,802	180	575	0	186
	C and *D*	0	66	108	5,077	40	268	0	50
	All	0	156	325	21,761	190	598	0	196
Weights on x_2		0.10	0.15	0.53	0.01	0.11	0.15	0.10	0.19

ecological benefits. As a result, the break-even points at which the EVPI or EVII of a project in terms of x_2 equals its annualized cost are 2.3, 11, 9.7, and 1.7 tons/yr of walleye for research projects *A, B, C,* and *D,* respectively. Lower interest rates, longer time horizons, or higher per fish values would decrease these thresholds. Table 10 shows that in most cases, the potential management benefits of the projects (EVPI) are well in excess of those break-even amounts of x_2. Therefore, all four research projects are potentially well worth their cost. Exceptions occur under two of the eight sets of value judgments: equal weights and person 1. There, EVPI is zero; their decisions would not alter if perfect information was available, no matter what set of prior probabilities is used.

Like the optimal fishery decisions discussed earlier, EVPI is also sensitive to value and probability judgments. Figure 5 shows a sensitivity analysis with respect to the same two judgments (w_8 and prior P(AZP=H)) we considered in the earlier sensitivity analysis (Figure 4). The EVPI in this case is calculated for all five parameters simultaneously, using the average weights and prior probabilities. By varying w_8 and P(AZP=H), Figure 5 shows that the EVPI can be three times as large as in the base case (196 tons, Table 10), or zero depending on the values of those two judgments. The figure reveals that EVPI is influenced by both, but that weight is the more important of the two, just as in the case of the strategies (Figure 4).

EVII Results

Information from research generally reduces uncertainty without eliminating it. Thus the actual value of information from research (EVII) is usually less than EVPI (and often considerably so). In Table 11, we present EVII for each of the four research projects for each combination of value and probability judgments considered in the earlier tables. (An exception is that we have eliminated the equal probabilities row as uninteresting. This is because an assumption of equal likelihoods $P(Z_{hk}|\delta_{nm})$ for each research outcome Z_{hk} would necessarily imply a zero EVII.) EVII is quantified in terms of walleye sport harvest, as in Eq. 12. In Table 11, the first, second, third, and fourth values in each entry indicate the EVII of projects *A*, *B*, *C*, *D*, respectively.

As anticipated, the values of imperfect information in Table 11 are generally less than the EVPIs of Table 10, sometimes equaling zero even though EVPI is positive. Larger discrepancies arise when the workshop participant anticipates that the research results will be unreliable (*i.e.*, a large likelihood that the research results will be inconsistent with the true state of nature/parameter value; see Table 5, above).

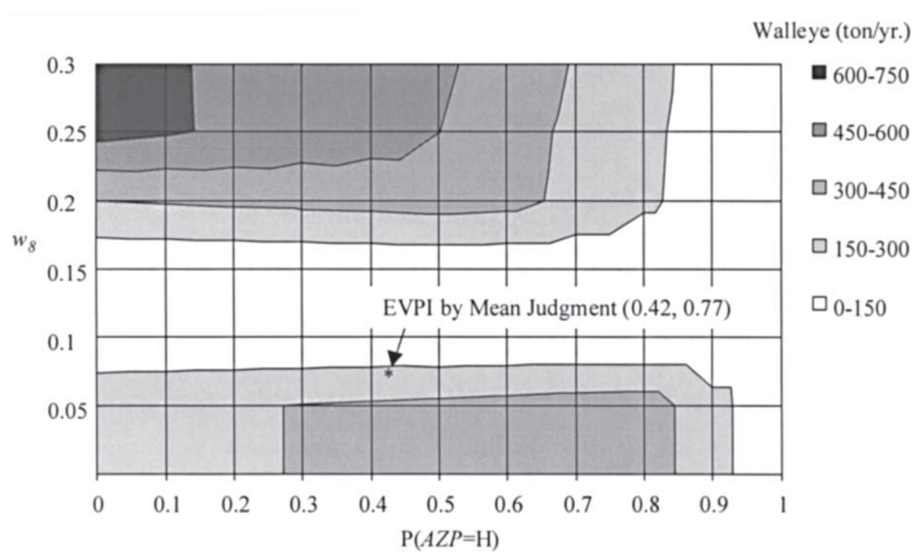


Figure 5. Sensitivity analysis for EVPI of eliminating uncertainty in all five parameters.

Table 11. EVII in terms of sport walleye harvest (ton/yr).

Person's probabilities	Research project	Person's value judgments 1	2	3	4	5	6	Equal	Mean
1	*A*	0	0	5*	0	0	0	0	_46*_
	B	0	0	_138*_	_5,060*_	0	0	0	21*
	C	0	0	87*	1,233*	0	0	0	0
	D	0	0	0	0	0	0	0	0
2	*A*	0	_113*_	_14*_	_6,211*_	_127*_	_109*_	0	_109*_
	B	0	82*	6	3,409*	80*	60*	0	80*
	C	0	17*	0	173*	0	0	0	6*
	D	0	10*	0	18*	0	0	0	0
3	*A*	0	0	0	0	29*	23*	0	27*
	B	0	_87*_	_37*_	_6,969*_	_190*_	_234*_	0	_186*_
	C	0	0	0	0	25*	21*	0	30*
	D	0	0	0	0	15*	20*	0	16*
4	*A*	0	_42*_	_427*_	_22,570*_	_59*_	_339*_	0	_120*_
	B	0	11	227*	12,226*	8	107*	0	32*
	C	0	0	70*	1,883*	0	4*	0	0
	D	0	0	67*	1,677*	0	0	0	0
5	*A*	0	0	0	0	_29*_	0	0	0
	B	0	0	0	0	30*	0	0	0
	C	0	0	0	0	12*	0	0	0
	D	0	0	0	0	1	0	0	0
6	*A*	0	0	0	259*	0	0	0	31*
	B	0	0	0	0	0	0	0	12*
	C	0	0	0	0	0	0	0	7*
	D	0	0	0	_2,850*_	0	_28*_	0	_53*_
Mean	*A*	0	26*	35*	3,150*	0	57*	0	0
	B	0	_46*_	_85*_	_6,871*_	_22*_	_201*_	0	_19*_
	C	0	17*	27*	930*	0	21*	0	0
	D	0	0	12*	139*	0	0	0	0
Weights on x_2		0.10	0.15	0.53	0.01	0.11	0.15	0.10	0.19

Note: An asterisk * indicates that EVII exceeds the estimated cost of project, assuming value of $12/walleye, a 10 year period and a discount rate of 10%. Italicized number indicates which of the four projects has the highest net benefits, using average estimated project cost.

Using the \$/walleye and interest rate assumptions of the previous subsection, we nevertheless find that for 31 of the 56 combinations of value and probability judgments, the research projects' benefits justify their costs. *A*, *B*, and *D* are each the highest benefit project for at least one combination apiece, while project *C* is never most valuable. *A* and *B* tend to have higher benefits than *C* and *D* because the former projects provide information on four of the five uncertain parameters in $\underline{\Delta}$, whereas the latter projects shed light on just two of the parameters.

Because we use walleye sport harvest to interpret EVII, we now illustrate a sensitivity analysis of the results with respect to the \$/walleye value. Based on the average value and probability judgments and \$12/walleye, the best research project is *B* whose EVII is 19 tons of walleye harvest per year. That project's net benefit (*i.e.*, the EVII minus the annual project cost from Table 4, assuming 10% interest and a 10-year benefit period) is positive if the value per walleye exceeds \$7.

Criteria weights too will affect a research project's net benefits. Figure 6 shows a sensitivity analysis of the net benefits of project *B* with respect to w_8 and prior P(*AZP*=H). The value in the figure represents net expected benefits from project *B* calculated by converting EVII to dollars using our \$/walleye value and 10% interest/10-year benefits period assumptions, and then subtracting the project cost of \$932,000. (Negative net benefit values are not shown.) With mean judgments (*i.e.*, w_8 = 0.07, P(*AZP*=H) =0.42, and mean likelihoods), the project's net benefit is \$107,000/yr. The diagram also shows that net benefits vary with the weight and prior probability.

CONCLUSION

Uncertainties about the impact of zebra mussels on energy and phosphorus flows in the lower trophic level of Lake Erie are large and potentially relevant to the

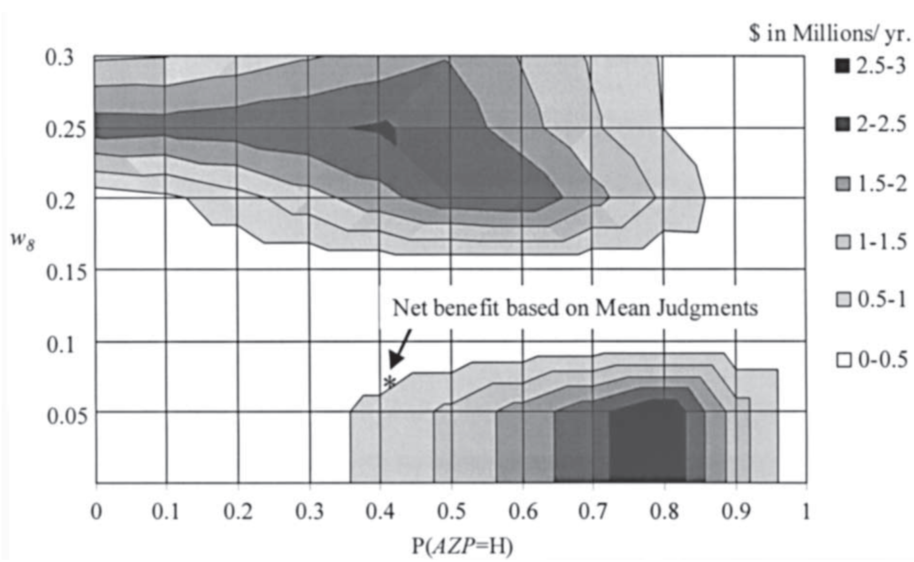


Figure 6. Sensitivity analysis of net value of Project B (EVII – cost) given mean judgments.

200642.pgs 1052 6/18/03, 10:48 AM

management of the lake's fisheries. In our analyses, we have shown that Bayesian and multicriteria decision analytic methods provide a practical approach for quantifying the implications of uncertainties for decisions and identifying the value of research for reducing them, while recognizing the multiple goals that concern managers and stakeholders. Although our representation of uncertainties is both limited and simplified, and we only had a limited number and range of experts in the workshop (six fishery scientists), two implications of our application of Bayesian methods stand out. First, our analysis shows that current uncertainties about the lower trophic level might hinder Lake Erie fisheries management. This is indicated by the results that show that the worth of removing those uncertainties (*i.e.*, EVPI) might be as much as thirteen times greater than the value of the annual walleye sports harvest. Second, the value to management of the imperfect information that research could provide (EVII) can be several orders of magnitude greater than the expense of research.

Our results support several additional insights. First, considering lower trophic level uncertainties can change decisions. For three out of the six participants in our workshop, the optimal targets for fishing mortality would change if they were to factor in those uncertainties. The expected improvement in the performance of fishery management resulting from recognizing uncertainty (ECIU) is as much as ten times the value of the historical annual walleye sport harvest. Averaged across the participants in our study, the performance difference between ignoring and including uncertainties in decisions is equivalent to approximately half of the historical walleye sport harvest. We also find that optimal fishery decisions and value of information are sensitive to expert judgments—both to probabilities representing the confidence managers have in alternative hypotheses about Lake Erie's lower trophic level and (especially) to the relative priority the managers assign to various ecological health and social objectives.

If Bayesian and multicriteria decision analysis methods are to be useful for ecological management, users must have confidence in the value and probability elicitation procedures required by those methods. Therefore, after the workshops, we asked the participating managers how easy, meaningful, and useful they found each of the workshop exercises. In general, the participants felt that value judgments, including definition of objectives and weight assessment, were easier and more meaningful than probabilistic judgments, including prior probabilities and likelihoods of research outcomes. This is reassuring, as the analysis results are most sensitive to weights. That the probability tasks were more difficult may be attributable to the fact that most of these managers lacked formal training and experience in Bayesian methods. The managers also stated that more time was desirable to discuss and quantify values, hypotheses, and uncertainties than was available during the two 1.5-day workshops. Therefore, we conclude that if value and probability judgments by experts and/or stakeholders are to be part of a quantified decision analysis of ecological research alternatives, adequate time (one week or more) should be allowed for the judgment elicitations tasks to ensure that the participants understand and have confidence in the methods and their results (Hobbs and Meier 2000).

ACKNOWLEDGMENT

We are grateful for the patient and good-humored participation of the fishery managers who provided the value and probability judgments. We also thank R. Anderson for his contributions to the multicriteria value assessment, A. Locci for her help in using LEEM, and D. Atkinson for his assistance during the workshop. Support for this work was provided by USEPA STAR grant R825150 and USEPA Region V grant X98540501. The usual caveats apply.

APPENDIX: LAKE ERIE ECOLOGIC MODEL LOWER TROPHIC LEVEL EQUATIONS

First, primary production (PP_t) [kg/yr] in year t is assumed to be a function of phosphorus loading and phosphorus internal recycling by zebra mussels:

$$PP_t = g_0\,(Pl_t + ZM_r\, N_{ZMt})^{g1}\,, \tag{14}$$

where Pl_t is phosphorus loading [kg/yr], ZM_r is a phosphorus recycling coefficient [yr^{-1}] for zebra mussel biomass N_{ZMt} [kg], and g_0 [ ] and g_1 [ ] are primary production coefficients. Mussel biomass in t in turn depends on biomass in $t\text{-}1$ and mussel production $ZmProd_t$ [kg/yr]:

$$N_{ZMt} = N_{ZMt-1}\,(1 - Z_{kz}\, N_{ZMt-1} - Z_{ka}\,) + ZmProd_t\,, \tag{15}$$

where Z_{kz} [kg^{-1}] and Z_{ka} [ ] are constants. $ZmProd_t$ [kg/yr] depends on PP_t and mussel biomass:

$$ZmProd_t = Z_{kp}\,[PP_t\,/\,(Z_K + PP_t)\,]\,N_{ZMt}\,, \tag{16}$$

with Z_{kp} [yr^{-1}] and Z_K [kg/yr] being constants.

Meanwhile, mussel biomass affects how much of the primary production consists of edible algae (PPE_t [kg/yr]):

$$PPE_t = [1 - N_{ZMt}^2\,/(\,N_{ZMt}^2 + \Phi_1^2\,)]\,(PP_t - ZmProd_t)\,, \tag{17}$$

where PPE_t [kg/yr] is edible algae biomass and Φ_1 [kg] is a constant. Zooplankton productivity [kg/yr] is a function of edible algae abundance:

$$ZooPP_t = AZP \times PPE_t\,, \tag{18}$$

where AZP [ ] is a constant. Since zebra mussels affect PPE_t , this implies an assumption that zooplankton compete with zebra mussels for food. Primary production available to the benthic zone ($BenFood_t$) [kg/yr] is a function of total primary less the production filtered by mussels:

$$BenFood_t = PP_t - \Phi_2\, ZmProd_t\,, \tag{19}$$

where Φ_2 [ ] is the Zoobenthos production coefficient. In turn, zoobenthos production ($ZooBP_t$) [kg/yr] is a function of benthic food availability:

$$ZooBP_t = AZB\ BenFood_t\,, \tag{20}$$

with AZB [ ] being a constant.

REFERENCES

Anderson RM and Hobbs BF. In press. Using a Bayesian approach to quantify scale compatibility bias. Manage Sci

Anderson RM, Hobbs BF, Koonce JF, *et al.* 2001. Using decision analysis to choose phosphorus targets for Lake Erie. Environ Manage 27(2):235-52

Barton A and Sergeant A. 1998. Policy before the ecological risk assessment: What are we trying to protect? Human Ecol Risk Assess 4(4): 787-95

Bella A, Duckstein L, and Szidarovszky F. 1996. A multicriterion analysis of the water allocation conflict in the Upper Rio Grande Basin. Appl Math Comput 77:245-65

Benjamin JR and Cornell CA. 1970. Probability, Statistics, and Decision for Civil Engineers, McGraw-Hill, NY, NY, USA

Bloczynski JA, Bogart WT, Hobbs BF, *et al.* 2000. Irreversible investment in wetlands preservation: optimal ecosystem restoration under uncertainty, Environ Manage 26(2):175-93

Clemen RT. 1995. Making Hard Decisions: An Introduction to Decision Analysis, Duxbury Press, California, USA

Council of Great Lakes Research Managers. 2000. In: Tulen LA and DePinto JV (eds), Great Lakes Modeling Summit: Focus on Lake Erie, Windsor, Ontario, Canada

Culver DA, Li H, Edwards W, *et al.* 2000. Ecological modeling of Lake Erie trophic dynamics-1999. In: Tulen LA and DePinto JV (eds), Great Lakes Modeling Summit: Focus on Lake Erie, pp. 65-70. Windsor, Ontario, Canada

Dahl JA, Graham DM, Dermott R, *et al.* 1995. Lake Erie 1993, western, west central and eastern basins: change in trophic status, and assessment of the abundance, biomass and production of the lower trophic levels. Canadian Technical Report of Fisheries and Aquatic Science No. 2070, Ontario, Canada

Dakins ME. 1999. Value of the value of information. Human Ecol Risk Assess 5(2): 281-9

Dakins ME, Toll JE, Small MJ, *et al.* 1996. Risk-based environmental remediation: Bayesian Monte Carlo analysis and the expected value of sample. Risk Anal 16(1):67-79

Dermott RM. 1993. Distribution and ecological impact of "Quagga" mussels in the lower Great Lakes. Electric Power Research Institute Technical Report. No. 102077, Ontario, Canada

Ellis JH. 1988 Acid rain control strategies: options exist despite scientific uncertainties. Env Sci Tech 22(11): 1248-55

Ellison AM. 1996. An introduction to Bayesian inference for ecological research and environmental decision-making. Ecol Appl 6(4):1036-46

Griffiths RW. 1999. Phosphorus, poisons and phyto-consumers: a synthesis of the factors affecting the western Lake Erie ecosystem over the past century. Presentation, Annual Meeting of the International Association for Great Lakes Research, Cleveland, OH, USA

Harboe R. 1992. Multiobjective decision making techniques for reservoir operation. Water Resour Bull 28(1):103-10

Hatch RW, Nepszy SJ, Muth KM, *et al.* 1987. Dynamics of the recovery of the western Lake Erie walleye (*Stizostedion –vitreum vitreum*) stock. Can J Fish and Aquat Sci 44(Suppl. 2):15-22

Heath RT, Sturtevant R, Shoup D, *et al.* 2000. Modeling the effects of nutrient concentrations on ecosystem stability: framework for a Great Lakes model. In: Tulen LA and DePinto JV (eds), Great Lakes Modeling Summit: Focus on Lake Erie, pp 37-50. Windsor, Ontario, Canada

Hobbs BF. 1997. Bayesian methods for analyzing climate change and water resource uncertainties. J Environ Manage 49:53-72

Hobbs BF and Meier P. 2000. Energy Decisions and the Environment: A Guide to the Use of Multicriteria Methods. Kluwer Academic Publishers, Norwell, MA, USA

Hobbs BF, Ludsin S, Knight RL, Ryan PW, *et al*. 2002. Fuzzy Cognitive Mapping as a tool to define management objectives for complex ecosystems. Ecol Appl, in press

Keeney RL and Raiffa H. 1976. Decisions with Multiple Objectives: Preferences and Value Tradeoff. John Willey, New York, USA

Kindler J. 1998. Linking ecological and development objectives: trade-offs and imperatives. Ecol Appl 8(3):591-600

Koonce JF and Locci AB. 1995. Final Draft Report on the Development of a Prototype Model for Lake Erie. Lake Erie Task Force, International Joint Commission, Windsor, Ontario

Koonce JF and Shuter BJ. 1987. Influence of various sources of error and community interactions on quota management of fish stocks. Can J Fish and Aquat Sci 44 (Suppl. 2):61-7

Koonce JF, Eshenroder RL, and Christie GC. 1993. An economic injury level approach to establishing the intensity of sea lamprey control in the Great Lakes. N Amer J Fish Man 13:1-14

Koonce JF, Busch WN, and Czapla T. 1996. Restoration of Lake Erie: contribution of water quality and natural resource management. Can J Fish and Aquat Sci 53(suppl. 1):105-12

Lake Erie Walleye Task Group. 1999. Report of the Lake Erie Walleye Task Group. Great Lakes Fishery Commission, Ann Arbor, Michigan, USA

Lindley DV. 1956. On a measure of the information provided by an experiment. Ann Math Stat 27(4):986-1005

Locci AB and Koonce JF. 1998. Effects of ecosystem constraints on single-species quota management in Lake Erie. Presentation, Annual Meeting of the International Association for Great Lakes Research, Cleveland, Ohio, USA

Locci AB and Koonce JF. 1999. A theoretical analysis of food web constraints on walleye dynamics in Lake Erie. In: Munawar M, Edsall T, and Munawar IF (eds), State of Lake Erie (SOLE) — Past, Present and Future. Backhuys Publishers, Leiden, Netherlands

Ludwig D, Hilborn R, and Walters C. 1993. Uncertainty, resource exploitation, and conservation: lessons from history. Science 260:17, 36

Manne AS and Richels RG. 1991. Buying greenhouse insurance. Energ Policy 19(6):543-52

Mardle S, Pascoe S, Tamiz M, *et al*. 2000. Resource allocation in the North Sea demersal fisheries: a goal programming approach. Ann Oper Res 94:321-42

McAllister MK and Peterman RM. 1992. Decision analysis of a large-scale fishing experiment designed to test for genetic effect of size selective fishing on British Columbia pink salmon(*Oncorhynchus gorbuscha*). Can J Fish and Aquat Sci 49:1305-14

McDaniels TL. 1995. Using judgment in resource management: a multiple objective analysis of a fisheries management decision. Oper Res 43(3):415-26

Morgan MG and Henrion M. 1990. Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis. Cambridge University Press, UK

Ohio Department of Health. 1999. Ohio Sport Fish Consumption Advisory. Columbus, Ohio, USA

Ohio Division of Wildlife. 1999. Ohio's Lake Erie fisheries, 1998. Ohio Department of Natural Resources, Division of Wildlife, Columbus, Ohio, USA

Peterman RM and Anderson JL. 1999. Decision analysis: A method for taking uncertainties into account in risk-based decision making. Human Ecol Risk Assess 5(2): 231-44

Reckhow KH. 1990. Bayesian inference in non-replicated ecological studies. Ecology 71(6):2053-9

Reckhow KH. 1994a. Importance of scientific uncertainty in decision making. Environ Manage 8:161-6

Reckhow KH. 1994b. A decision analytic framework for environmental analysis and simulation modeling. Environ Toxicol Chem 13 (12):1901-6

Ridgley MA and Rijsberman FR. 1992. Multicriteria evaluation in a policy analysis of a Rhine estuary. Water Resour Bull 28(6):1095-110

Rothley KD. 1999. Designing bioreserve networks to satisfy multiple, conflicting demands. Ecol Appl 9(3):741-50

Sainsbury KJ. 1991. Application of an experimental approach to management of a tropical multispecies fishery with highly uncertain dynamics. ICES Mar Sci 193:301-20

Talhelm DR. 1988. The international Great Lakes sport fishery of 1980. Great Lakes Fishery Commission, Special Publication No. 88-4, Ann Arbor, Michigan, USA

Varis O and Kuikka S. 1999. Learning Bayesian decision analysis by doing: lessons from environmental and natural resources management. Ecol Model 119:177-95

Venkatesh BN and Hobbs BF. 1999. Analyzing investments for managing Lake Erie levels under climate change uncertainty. Water Resour Res 35(5):1671-83

Walters CJ and Hilborn R. 1976. Adaptive control of fishing systems. J Fish Res Board Can 33:145-59

Walters CJ. 1986. Adaptive management of renewable resources. Macmillan Press, New York, USA
Walters CJ and Green R. 1997. Valuation of experimental management options for ecological systems. J Wildlife Manage 61(4):987-1006
Watson SR and Buede DN. 1987. Decision Synthesis. Cambridge University Press, UK
Wolfson LJ, Kadane JB, and Small MJ. 1996. Bayesian environmental policy decisions: two case studies. Ecol Appl 6(4) 1056-66